Mind the Gap: A Difference-in-Difference Analysis of the Heterogeneous Effects of Paid Family Leave Policies on Women's and Men's Earned Income in the United States

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Abstract

Since 2004, four states have begun to offer paid family leave benefits intended in part to improve labor outcomes for women as they often take on the additional burden of caregiving responsibilities. Using American Community Survey data, we analyze the effect of these policies on the gender wage gap and find results consistent with these intentions. Employing a difference-in-difference design, our analysis finds significant increases in female earnings relative to men, as well as hours worked, in states with paid family leave policies. These results remain positive across racial groups and demonstrate particularly strong effects among women who gave birth in the past year.

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1. Introduction

The gender wage gap is a serious and persistent issue in America. While discrimination on the basis of sex is illegal in the United States, wages in this country remain unequal between women and men even when controlling for compensable factors. According to 2018 data from the US Census Bureau, the median earnings of women working full time is 18% lower than their male counterparts. Unfortunately, the wage gap grows even larger when considering women of color against white men. Latinx women earned only 54 cents for every dollar earned by white men (2018 American Community Survey (ACS) 1 Year Estimates, 2019). Policy makers view well-crafted family leave policies as a potential solution to improve labor force participation among women by ensuring that they are able to take paid leave to care for family members and then return to their jobs. Because there is not a federal level policy, states have taken the onus upon themselves; California passed a state-level paid family leave policy in 2004, and since that time several other states have passed legislation and begun offering paid-leave benefits.

Our paper seeks to analyze the impact of paid family leave on the gender wage gap in the four states (California, New Jersey, New York, and Rhode Island) that launched paid-leave programs before 2019. We conducted a difference-in-difference regression analysis to examine the policy's impact on the wage gap. We gathered data from the American Community Survey (ACS) for the years 2000, 2006, 2012, and 2019 in order to have observations for years before and after each of the states implemented this policy.¹ Our dataset includes economic outcomes and demographic information at the individual level for millions of Americans. The ACS provides us with a robust sample size, even when disaggregating for states, gender, year, and other factors.

Our analysis compares the four states that have passed the policy both to the entirety of the United States and to a “common support region” that we established through generating propensity scores to predict the likelihood that any given state would adopt the family leave policy. After the comparison groups were established, we ran a series of regressions to home in on the differential effect of the policy on earned income by sex, as well as its impact on hours worked and employment status to contextualize our main results. A subset of these models contain interaction terms to test for further effect heterogeneity across factors such as age and race.

Across our models we find similar results: paid family leave policy has a significant effect on shrinking the gap in earned income between women and men. Limiting our observations to the common support region, we estimate that paid family leave policy narrows this gap by 7.4% ($p < .001$). Adding a control for usual hours worked attenuates the magnitude of the policy effect. Furthermore, we estimate that paid leave policy increases women's usual hours

¹ California offered benefits starting in 2004, New Jersey in 2009, New York in 2018, and Rhode Island in 2013.

worked relative to men by 1.072 hours ($p < .001$), indicating that increases in women's relative earned income are driven, at least in part, by increases in their relative hours worked. Further analysis examining the policy's heterogeneous effects by race indicates that the policy has a lesser effect on gender pay gaps among men and women who identify as Black and among those who identify as non-white Hispanic. These differential effects are influenced by the relatively smaller gender pay gaps observed in these groups at baseline.

One potential issue that may impact our results is that family leave programs are not uniform across the small set of treated states. Programs differ by leave length, benefit amount, eligibility requirements (amount earned, weeks worked), and funding approach (employee, employer). Our analysis flattens these differences into a binary indicator representing if a paid leave program is in effect for a given state and does not tease out the potential differential impacts of program variations. While our analysis considers each state's policy to be equivalent, it is important to note that these policies may have different impacts in their states because they offer different benefits.

Another potential issue that complicates our results is that as paid leave policy goes into effect, states may experience a lag in uptake as eligible workers are educated about their new benefits. Policies may become more effective in closing the wage gap over time as knowledge and uptake increases. Additionally, since the dataset does not contain a variable indicating if an individual claimed paid leave benefits, the model reflects an intent-to-treat analysis (versus impacts on income for individuals who have taken paid leave).

Finally, our analysis is also limited to analyzing gender as a binary variable (male or female). Accordingly, our data does not support an analysis that differentiates the impact of this policy for gender non-binary or genderqueer individuals. We hope that in the future data will incorporate these gender identities as options for self-reported gender identity. Our understanding of economic and other outcomes for gender non-binary and genderqueer individuals would improve if surveys take steps to be more inclusive.

2. Background

Unlike most other wealthy nations, the United States does not guarantee paid parental leave at the national level. In the absence of a federal policy, states drive paid family and medical leave policy in the US. While specifics differ, state policies generally allow employees to take leave from their jobs to bond with a new child or care for themselves or a family member while receiving benefits equivalent to a portion of their salary. Programs vary by state on multiple dimensions, including length of leave, benefit amount, eligibility requirements (amount earned, weeks worked), and funding approach (employee, employer). Effective in 2004, California built their program off the statewide temporary disability insurance program. New Jersey (2009), Rhode Island (2014) and New York (2018) followed suit. Programs in DC and Washington have gone into effect this year, while Massachusetts,

Connecticut and Oregon have enacted paid family leave laws that will go into effect in the coming years.

EXHIBIT 1:
FIRST YEAR OF PAID FAMILY LEAVE AVAILABILITY FOR EACH STATE

State	California	New Jersey	Rhode Island	New York
Year Benefit Availability Begins	2004	2009	2013	2018

Paid family leave policy was enacted in these states based on the believed economic and health benefits as well as the flexibility that it offers people during challenging times when they must care for members of their families. Caretaking responsibilities disproportionately fall on women, often necessitating their departure from formal employment. In taking leave from paid employment to care for a newborn or sick relative, many women in the US forfeit their current wages (absent an employer-specific or state-based policy). Beyond the immediate wage impact, gaps in women's formal employment history can hurt their future earnings relative to their male peers if or when they return to the workforce. Keeping women in the labor force is therefore an outcome of interest for women's economic equality. One study on the paid family leave policy in California showed an 8 percent increase in labor force participation in the short term (2003 - 2006) and a 14 percent increase in labor force participation in the long term (2003 - 2011) of unpaid care providers (Skira, 2015).

There is an existing body of research on the impacts of paid family leave policies in the U.S. that assesses the effects policies have had on individual and individual and firm-level economic outcomes including labor force participation, hours worked, and job turnover rates, especially for women. Other research has evaluated the policy's impact on neonatal and maternal health outcomes. Existing research has already tied paid-leave policies to increased employment and labor force participation, and some policy makers believe that these policies could help to reduce the gender wage gap as well. While a number of factors influence the gender wage gap, labor force participation is believed to be one of the major contributors.² Our analysis attempts to build on this existing research to provide new insights on if paid family leave may also work to decrease the gender wage gap.

The analysis in this paper is also novel because it will be the first to incorporate new 2019 data from the U.S. Census Bureau into analysis of paid family leave and the wage gap. Incorporating new data into this analysis is especially important because many of these benefits have become available only recently, for example New York only began to offer benefits in 2018. There may be some lag before people become aware of these state benefits and take up may increase over time, which could shift the effect of the policy on the wage gap and other important outcomes. A smaller benefit of incorporating the new data into our analysis is that for states including Connecticut, Massachusetts, Oregon, and Washington,

² Some of the other prominent factors include: differences in the industries and jobs worked between men and women, differences in hours worked across gender lines, and gender discrimination in the labor market

this will be one of the last years to observe these states' outcomes before their paid-leave programs are rolled out and residents are eligible for benefits.

As paid leave policies are put on ballots, debated in state legislatures or added to candidate platforms, examining the impacts these programs have on the gender wage gap can help inform policymakers and advocates who are working to improve workforce outcomes for women in their states and in this country. An important consideration of our research is that paid-leave policies' impacts on the gender wage-gap should not be viewed as the sole criterion on which the merit on which the policy is judged. While decreasing the gender wage-gap is potentially an important benefit of the policy, it delivers other key beneficial outcomes that are outside of the scope of this paper. Our analysis will try to build on the existing research about these policies but will focus narrowly to glean new insights on if paid family leave is successful in decreasing the gender wage gap.

3. Conceptual Framework

By instituting a legal and financial framework for caregivers to take compensated, short-term leave from formal employment, paid leave programs may allow women to remain in the workforce instead of dropping out entirely to fulfill caregiving duties. Beyond the immediate wage impact this has from simply remaining employed, we posit that staying in the workforce allows women to experience the high wage growth that workers commonly experience during their 20s and 30s, which are also primary childbearing years. Furthermore, young women may be enticed to work in the formal sector or chose different career paths than they otherwise would with the knowledge that paid leave will be available to them if they decide to have a child in the future. We therefore hypothesize that paid leave policy will have a differential impact on women's earned income compared to men's, narrowing existing gender wage gaps for treatment states (see Exhibit 2).

EXHIBIT 2: GENDER WAGE GAP IN THE YEAR 2000

However, this policy could fail to impact the gender wage gap for a number of reasons. The benefit may entice women to take a leave of absence from work and they may decide not to return to formal employment when the benefit period expires. Additionally, it may be too early for this analysis to detect an effect on earnings in states that have recently passed the policy, such as New York. Furthermore, by encouraging caregivers (women) to take leave, the policy may have unintended consequences on firms' desire to hire childbearing age women, leading to discrimination in the labor market. Finally, paid leave programs are available to both women and men. If uptake does not differ along sex lines, earnings effects could be similar for both sexes and we would fail to see a change in existing gaps.

4. Data

Our primary data source is the American Community Survey, using the most recent year available (2019) as well as earlier surveys from 2000, 2006, and 2012 to examine the change over time. During the course of our analysis the 2019 ACS data became available and we opted to break the every-six-year pattern to use this data instead of data from 2018. Using this data allowed us to analyze impacts on New York a full year after the benefits became available rather than during the first year of the policy during which policy uptake may have been lower. As discussed previously, using this data also helps this analysis to contribute novel findings to the body of research on paid family leave.

One of the main benefits of using this dataset was that the ACS has consistently collected the economic and demographic data for decades, allowing us to look at the primary impacts of paid family leave across different outcomes. The ACS provides us with a robust sample size, which allows us sufficient statistical power even when controlling for several different

factors. Within the ACS, our primary variables of interest will be: earned income, gender, year, hours worked, and race. Our model will also control for education attainment, labor force status, metropolitan status, marital status, and industry (discussed further under Methods).

We limited our observations to the ages of 23 to 64 to approximate the age group that is most likely to be working. We chose the upper bound of 64 because this is the age before people qualify for Social Security benefits. We do recognize that some Americans retire before reaching that age, and unfortunately even more cannot afford to retire even after they become eligible for those benefits, but we wanted to choose an upper bound that best approximated retirement age. We chose the lower bound of 23 to remove populations that were most likely to not work because they are pursuing education from the sample.

Most of our regression analysis is based on the logarithm of earned income, as opposed to gross earned income because the distribution of earned income is skewed strongly to the right tail. In order to run our regressions on a normally distributed set of data, we opted to use the log of earned income as our main outcome of interest. Because log earned income drops values from our dataset when earnings were zero, we first analyzed the policy's impact on employment and labor force participation. If our results had shown that employment or labor force participation had decreased in states with paid leave policy relative to those without, it could have called into question the factors that were leading to a change in our log earnings, but our analysis showed that women were more likely to be employed and working in states where these policies have been enacted.

The log of earned income is based on the ACS' earned income variable, which represents individual earnings collected from wages or from a person's business or farm in the last year. This variable does not factor in other income including investment and any government support programs (including paid family leave benefits).

TABLE 1:
SUMMARY STATISTICS FROM BASELINE TO MOST RECENT YEAR

	2000			2019		
	All States	Common Support	Treatment States	All States	Common Support	Treatment States
Earned Income (Male)	\$41494.9 (49863.0)	\$45275.5 (55206.1)	\$46688.4 (58331.9)	\$60114.0 (81086.2)	\$67577.4 (92529.1)	\$69440.3 (97625.4)
Earned Income (Female)	\$21119.8 (26672.7)	\$23718.5 (31666.3)	\$24424.1 (33094.0)	\$36495.1 (51207.9)	\$42269.3 (59832.7)	\$43317.7 (43317.7)
Log Earned Income (Male)	10.36 (.98)	10.42 (1.01)	10.43 (1.02)	10.72 (1.08)	10.80 (1.11)	10.81 (1.12)
Log Earned Income (Female)	9.78 (1.12)	9.88 (1.13)	9.92 (1.14)	10.33 (1.11)	10.16 (1.13)	10.47 (1.13)
Hours Worked (Male)	40.13 (16.92)	39.38 (16.96)	39.22 (17.06)	35.63 (19.11)	35.29 (18.58)	34.97 (18.54)
Hours Worked (Female)	29.52 (18.61)	28.81 (18.77)	28.47 (18.99)	28.28 (19.10)	28.26 (18.94)	27.98 (19.04)
Labor Force Participation (Male)	.85 (.36)	.85 (.36)	.84 (.36)	.81 (.39)	.82 (.38)	.83 (.38)
Labor Force Participation (Female)	.71 (.45)	.71 (.46)	.69 (.46)	.73 (.44)	.74 (.44)	.74 (.46)
Employment Status (Male)	.80 (.40)	.79 (.41)	.79 (.41)	.77 (.42)	.78 (.41)	.78 (.45)
Employment Status (Female)	.66 (.47)	.65 (.48)	.64 (.48)	.69 (.46)	.70 (.46)	.69 (.48)
Bachelors Degree Attainment (Male)	.30 (.46)	.34 (.47)	.34 (.47)	.33 (.47)	.38 (.48)	.38 (.49)
Bachelors Degree Attainment (Female)	.29 (.45)	.32 (.47)	.32 (.46)	.39 (.49)	.43 (.50)	.43 (.50)
Percent White	76.39	70.26	63.44	67.23	59.22	50.51
Percent Black	8.84	7.13	7.44	9.37	6.44	7.21
Percent Hispanic/Latino	8.63	13.27	17.41	14.24	19.67	25.03
Percent Asian/Pacific Islander	4.22	7.43	9.71	6.31	11.56	14.43
Percent Native American	0.66	0.51	0.45	0.84	0.69	0.34
Percent Multiracial/Other	1.26	1.4	1.55	2	2.42	2.48

Note: Standard Deviations in parentheses.

To provide context to our results, we also estimate the policy effects on usual hours worked, labor force participation, and if people were currently working. Hours worked represents the number of hours that respondents usually work in a single week, if they worked in the last year. Labor force participation represents whether or not respondents are actively employed or actively seeking employment. For the purposes of our analysis, we defined people who were actively working or actively in the military as “working.”

Race is an important control in our model and is also incorporated into alternate versions of our regressions to assess the policy’s heterogeneous effects. We used the ACS demographic data to create a series of mutually exclusive racial categories. Respondents were assigned to one of “White” “Black” “Hispanic/Latino” “Asian/Pacific Islander” “Native American” or “Multiracial/Other” based on their responses to ACS survey questions. While these categories do help to demonstrate some of the unequal racial impacts of the policy, we should note that inside of many of these categories there may be further heterogeneity based on other factors such as nationality, immigration status, and language ability. For example, economic outcomes for Chinese Americans and Cambodian Americans tend to be different, though both fall into the broader category of Asian/Pacific Islander.

Finally, our policy variable is a binary indicator specifying if a state has a paid family leave insurance program in effect for the given year. Here, “in effect” means that eligible workers can claim the benefit, rather than meaning that the law has been passed. There are a number of states that have currently passed the law, but where people cannot yet take paid leave.

5. Methods

This analysis seeks to find an unbiased estimate of state paid family leave policies on female earnings and ultimately the gender wage gap. Naturally, these estimates are easily confounded by omitted variable bias and other underlying statewide characteristics that influence female wage outcomes beyond the passage of a paid family leave policy. Due to the infeasibility of a randomized controlled trial, this analysis creates propensity scores for each state, effectively using statewide characteristics from the year 2000 to predict the likelihood of a state adopting a paid family leave policy.³

After establishing propensity scores, we then matched our treated units — states that pass paid family leave policies — with states with similar underlying characteristics in order to create a common support region. Dehija and Wahba (2002) established that focusing on this smaller subset of the control states comparable to the treated states acts to diminish the bias that arises due to underlying differences between the treated states and the broader comparison states. As a result, we expect that differences in the female wage outcomes between treated and matched states serve to indicate the true causal effect of paid family leave policies. Though many propensity scores methods match on a 1:1 basis (Austin, 2011), our analysis operates with a 10-state common support region in order to allow for greater statistical power in our estimates.

³ See Table 2 for complete list of statewide characteristics

TABLE 2
BALANCE BETWEEN "TREATMENT" AND "CONTROL" STATES IN YEAR 2000

State-level variable	Full 51-state sample		"Common support" sample	
	Ever-adopters	Never-adopters	Ever-adopters	Never-adopters
Percent Rural	8.2 (1.7)	29.4*** (2.1)	8.2 (1.7)	15.9 (3.9)
Percent Black	10.2 (2.7)	10.9 (1.7)	10.2 (2.7)	13.7 (9.3)
Percent White	71.2 (5.3)	79.1 (2.1)	71.2 (5.3)	72.6 (8.8)
Percent Asian	6.1 (1.7)	2.6 (.86)	6.1 (1.7)	2.9* (.63)
Percent of population that is women aged 18-50	23.7 (.12)	23.3 (.13)	23.7 (.12)	23.9 (.70)
Per Capita Income	\$23698.5 (1156.6)	\$20685.8** (435.1)	\$23698.5 (1156.6)	\$22777.50 (1654.4)
Birth Rate (per 10,000 population)	135.5 (6.8)	137.9 (2.6)	135.5 (6.8)	131.5 (4.1)
Infant Death Rate (per 10,000 live births)	61.25 (3.19)	71.9 (2.3)	61.25 (3.19)	67.3 (8.4)
Percent of population with a bachelor's degree	22.6 (.95)	19.5 (.58)	22.6 (.95)	23.2 (2.2)
Employment Rate	93.6 (.38)	94.4 (.19)	93.6 (.38)	93.2 (.88)
Percent of workers in manufacturing industry	12.9 (1.3)	13.2 (.79)	12.9 (1.3)	10.6 (2.2)
N	4	47	4	6

Note: Standard errors in parentheses.

*** Denotes a coefficient significant at the 1% level; ** the 5% level; * the 10% level (in comparison to treatment states)

Table 2 demonstrates the significantly more similar baseline characteristics of our matched control states when compared to all states broadly. Further, 4 of the 5 states to adopt paid family leave since 2018 are included in our matching model as well.⁴ This lends credibility to the parallel trends assumption underlying our difference-in-difference regression approach. Our loss in statistical power in trimming our unit of observation to only 10 states is offset by increased confidence that our results are unbiased.

Table 3 illustrates the results of our propensity score regression. After creating predicted probabilities of passing paid family leave policies from this regression, we saw minimum likelihood of passing a policy of 20.9% and a maximum likelihood of 43.4%. This fairly wide bandwidth allowed for 6 states in the common support region.

⁴ Our common support region includes DC, Massachusetts, New Mexico, Pennsylvania, Oregon, and Washington, in addition

TABLE 3: PROPENSITY SCORE MODEL
PREDICTING WHETHER A STATE ADOPTS A POLICY

State-level variable	Coefficient
Percent Rural	-.99** (.47)
Percent Black	-.76 (1.03)
Percent White	-.73 (1.11)
Percent Asian	-1.02 (1.77)
Percent of population that is women aged 18-50	2.59 (8.77)
Per Capita Income	-.00002 (.00003)
Birth Rate	-.0053 (.003)
Infant Death Rate	-.0033 (.0044)
Percent of population with a bachelor's degree	.902 (2.37)
Employment Rate	-4.62 (5.08)
Percent of workers in manufacturing industry	1.62 (1.01)
N	51
R ²	0.2821

Note: Standard errors in parentheses.

*** Denotes a coefficient significant at the 1% level; ** the 5% level;

* the 10% level.

Our difference-in-difference models estimate the policy's heterogeneous impact on the logarithm of women's earned income relative to men's via the interaction term *Policy x Female*. The main models include controls for individual, state, and year fixed effects. We estimate a weighted regression, using sample weights from the ACS. In order to prevent understating the standard deviation of estimated treatment effects, our model used robust standard errors, clustered at the state level (Bertrand, Duflo, & Mullainathan, 2004). Our main models are divided between observations from all 50 states and D.C. and from the common support region⁵. Within each observation group, we run an alternative set of analyses that further limits the sample to a likely childbearing age (23-36). We estimate an equation of the form, where Y represents the outcomes for individuals i , residing in state s , at time t . T is an indicator of whether or not a state had adopted the paid-leave policy at time t . G is an indicator of gender for individual i . X is a vector of individual level variables, and ε is the normally distributed error term.

$$Y_{ist} = \alpha_s + \alpha_t + \beta_1 T_{st} + \beta_2 G_i + B_3(T_{st} \times G_i) + BX_{ist} + \varepsilon_{ist}$$

Our analysis used the interaction term $B_3(T_{st} \times G_i)$ to isolate the differential effect of the paid-leave policy on women compared to men.

⁵ We estimated alternate versions of our regression models looking at all 50 states and Washington, D.C. as well as a trimmed set of observations restricted to treatment and control states identified by the propensity score matching method. While the trimmed version supports covariate balance, clustered standard errors are larger because of the small number of clusters that are available. Including observations from all 51 states (and D.C.) has more clusters, and thus smaller standard errors, but sacrifices covariate balance, introducing potential bias.

6. Results

As discussed in the conceptual framework, we hypothesize that paid leave policy will have a differential impact on women's earned income compared to men's, thereby narrowing the gender wage gaps for treatment states. Accordingly, the outcome of interest is the heterogeneous effect of the policy on the logarithm of earned income by sex. Estimations from the four main sets of models tell a similar story — paid family leave policy has a significant effect on shrinking the gap in earned income between women and men in treatment states.

TABLE 4
OLS ESTIMATES: EFFECT OF PAID FAMILY LEAVE ON LOG EARNINGS

	All States				Common Support Region			
	Broad Observations		Age Limited (23-36)		Broad Observations		Age Limited (23-36)	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
PFL	0.063*** (.018)	0.107*** (.017)	0.043*** (.013)	0.09*** (.013)	-0.011 (.025)	0.028 (.022)	-0.028 (.021)	0.017 (.022)
Female	-.405*** (.006)	-0.227*** (.004)	-0.329*** (.007)	-0.169*** (.005)	-0.406*** (.012)	-0.214*** (.009)	-0.313*** (.012)	-0.149*** (.011)
PFL*Female	0.075*** (.009)	0.039*** (.006)	0.082*** (.012)	0.036*** (.011)	0.074*** (.011)	0.025** (.010)	0.063*** (.013)	0.016 (.011)
Usual Hours Worked		0.035*** (.0004)		0.036*** (.0004)		0.036*** (.0004)		0.037*** (.0002)
Bachelors' Degree	0.517*** (.006)	0.452*** (.006)	0.488*** (.010)	0.416*** (.007)	0.525*** (.008)	0.447*** (.007)	0.506*** (.015)	0.41*** (.011)
English Ability	0.340*** (.018)	0.314*** (.017)	0.319*** (.017)	0.301*** (.018)	0.37*** (.022)	0.352*** (.014)	0.331*** (.027)	0.336*** (.018)
Metropolitan Status	0.180*** (.018)	0.186*** (.011)	0.162*** (.011)	0.165*** (.011)	0.206*** (.019)	0.204*** (.018)	0.195*** (.019)	0.188*** (.018)
Marital Status	0.218*** (.004)	0.202*** (.003)	0.233*** (.006)	0.201*** (.006)	0.22*** (.010)	0.206*** (.006)	0.241*** (.011)	0.21*** (.011)
N	51	51	51	51	10	10	10	10
R2	0.2902	0.4191	0.2834	0.4175	0.2901	0.4205	0.2849	0.419

Note: standard errors, clustered by state, in parentheses. All models weighted using probability sample weights. All models include the following control variables: age, employment status, industry, & race, as well as state and year fixed effects.

*** Denotes a coefficient significant at the 1% level; ** the 5% level; * the 10% level.

Analyzing observations from the common support region, the simple model controlling for individual, state, and year fixed effects estimates that paid family leave policy narrows the earned income gap between women and men by 7.4% ($p < .001$). Adding a control for hours worked attenuates the magnitude of the policy effect, however it is still positive and significant at a 95% confidence level (2.5%, $p = 0.029$). The impact of adding this control to the model indicates that hours worked is a mediating variable of the policy's effect on earnings, further confirmed by our contextual analysis, discussed below. We estimate similar results when looking at our full sample of all 50 states and D.C (See Table 4).

Limiting the analysis to a narrower subset of observations of likely childbearing age (23-36)⁶ in the common support region, the estimated policy effect diminishes somewhat to 6.4% ($p = 0.001$) and results are not significant when controlling for hours worked. Here results differ between the common support region and all states; the policy effect increases slightly

⁶ The likely childbearing age of 23-36 was calculated as one standard deviation from the mean age of women who gave birth in the last 12 months.

when limiting observation to 23- to 36-year-olds in all states and the policy continues to have a positive, significant impact on relative earnings when controlling for hours worked.

We further examined the policy's heterogeneous effects by race, introducing three-way interaction terms of the policy, sex, and each racial group to the model.⁷ In this model, the estimated effect of the policy on the white gender pay gap is 7.2% for observations from the common support region. We do not see a distinguishable difference in the policy's impact on the Asian, Native American, or multiracial gender wage gaps relative to the White gap. However, the policy effect shrinks to about 1% ($p=.002$) on the earned income gap between non-white Hispanic women and men and near zero ($p=.035$) for the gap between Black women and men. Here it is important to note that baseline gender pay gaps differ starkly between racial groups. As shown in Figure 3, earned income gaps between Black women and men and non-white Hispanic women and men are relatively smaller than that between White women and men, particularly driven by differences in men's earnings by race.

⁷ Our analysis also explored if the policy had heterogeneous effects by age, using a triple interaction term of policy, sex, and age. Results across the four main models (common support region and all states, with alternate versions limiting to childbearing age) were not significant.

TABLE 5
TESTS FOR RACIAL EFFECT HETEROGENEITY IN LOG EARNINGS

Variable	All State	Common Support
PFL	0.096*** (.021)	0.009 (.032)
Female	-0.464*** (.006)	-0.465*** (.010)
PFL*Female	0.071*** (.013)	0.071*** (.009)
PFL*Black	-0.013 (.019)	-0.043 (.029)
Black*Female	0.294*** (.011)	0.335*** (.028)
PFL*Black*Female	-0.038** (.019)	-0.079** (.032)
PFL*Hispanic	-0.051*** (.017)	-0.006 (.029)
Hispanic*Female	0.12*** (.013)	0.131*** (.009)
PFL*Hispanic*Female	-0.048*** (.017)	-0.06*** (.014)
PFL*Asian	-0.059*** (.017)	-0.027 (.034)
Asian*Female	0.136*** (.013)	0.148*** (.019)
PFL*Asian*Female	-0.002 (.017)	-0.015 (.021)
PFL*Native	-0.022 (.037)	0.016 (.079)
Native*Female	0.201*** (.034)	0.167 (.104)
PFL*Native*Female	-0.118* (.061)	-0.085 (.128)
PFL*Multi	-0.038** (.018)	-0.043 (.033)
Multi*Female	.164*** (.018)	0.165*** (.023)
PFL*Multi*Female	-0.013 (.031)	-0.015 (.042)
N	51	10
R ²	0.2922	0.2918

Note: Standard errors in parentheses.

*** Denotes a coefficient significant at the 1% level; ** the 5% level; * the 10% level.

To provide context to the findings from our main models, we examined the effect that the policy had on women's hours worked relative to men. Paid leave policy is estimated to increase women's usual hours worked relative to men by 1.072 hours ($p < .001$) and the effect increases slightly when limiting observations to childbearing age. This confirms indications from the alternative versions of our main model, that usual hours worked is a mediating variable on the causal pathway of the policy's differential effect on earned income.

For further context, we also estimated policy effects on a subset of observations limited to women who gave birth in the last 12 months across all 50 states and D.C. The policy did not have a significant effect on their hours worked. However, paid leave policy is estimated to increase earnings for recent mothers by 11.6% ($p < .001$). Additionally, while the policy does not have a significant effect on labor force participation for these women, it does increase the proportion who reported having a job but not working by an estimated 2.67% ($p < .001$), which could indicate that women are taking advantage of temporary leave and remaining in the labor force.

7. Conclusions

Our analysis finds significant positive effects of paid family leave policies on women's earned income and hours worked relative to men across both all states broadly as well as the common support region. These conclusions are robust across multiple controls. While White women see the largest benefits from paid family leave policies, we find that women of color still see positive effects in the aggregate, and no racial group is definitively worse off as a result of the policy. Given that our dataset did not include information on take-up of the policy, it should be treated as an intent-to-treat analysis, as we have no way of knowing which women took leave and which did not.

Our analysis also finds strong evidence that paid family leave policies are working as intended. Among women who recently gave birth, we found a significant increase on leave from work in states with paid family leave policies. Further, wages among these new mothers consistently remain significantly higher in states with paid family leave policies. These results demonstrate these policies' promise in creating a more gender-equitable society.

Since the timeframe of this analysis, five states and Washington D.C. have paid leave laws that are now in effect or will be in the near future (including Colorado, which passed paid leave in the November 2020 election). As paid leave expands, research can continue to examine the differential impacts that program designs have on uptake and women's health and economic outcomes, informing the structures of new programs. Further research analyzing the impact of paid leave policy on the relative burden of care and incidence of leave-taking between women and men will also be instructive in assessing the policy impact on economic equality.

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